Dynamic task assignment for a multi-robot system based on the Attractor Selection Model

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Abstract

Biological systems are often made up of many well-organized elements, some examples are swarm behavior or cell differentiation over the developing process of animals. On the other hand, it is difficult to develop a multi-robot system like a biological system which could be flexible and adaptable to environmental changes. Recently, it is suggested that fluctuations within biological systems play an important role in order to achieve such flexibility and adaptability. In this report, we propose a new control method for dynamic task assignment of multi-robot cooperation inspired by the adaptability of a biological system and we apply our proposed method in a cleaning task within a dynamic environment.

1. Introduction

Dynamic task assignment is an essential requirement for multi-robot system operation. Traditionally, task assignments were considered in a centralized way. A controller gathers all the relevant information such as the position of all robots and objects, and allocates tasks to every robot [1, 2]. The weakness of this approach is that the accuracy of global information is not always possible to obtain, and such system is often hard to maintain because any failures to the controller will paralyze the entire organization. Hence, increasing attention has been paid to the study of distributed multi-robot systems which have no centralized control. There are many approaches, in which the robots coordinate their actions through deliberate communications and negotiations [3, 4, and 5]. Such approaches are primarily used in systems consisting of a relatively small number of robots (i.e., fewer than 10), due to scaling issues. Task assignment through intentional coordination remains the preferred approach because it is better understood, easier to be designed and implemented. However as the number of robots increases, the complexity of the design of intentional approaches increases due to the demands in communication bandwidth and computational abilities of individual robots.

Hence new approach without deliberate communications and negotiations is necessary for task assignment of multi-robot system. Although the modelling and control of the system becomes harder as the number of robots increases or its environment becomes more complex, each robot have to change its behavior according to its situation. In order to adapt to environment changes, robots need an enormous amount of behavior rules for every single situation the robot could face, because robots cannot operate within a situation they have not already considered. Therefore, it is difficult to design control rules for multi-robot systems which operate in real environments. Especially when there are a large number of robots within an environment that changes frequently. The learning process of such control rules is difficult due to the fact that there is a large number of an unfamiliar situation in which the robot has no previous experience. In order to overcome these problems we tried to get some hints from the nature.

Biological systems are well known for their potential to adapt to a new, unknown, and noisy environment. The mechanism of such flexible adaptation is investigated especially in molecular biology, and the importance of the biological fluctuation is made clear [6]. The fluctuation in molecular biology is actually a noise due to the heat fluctuation, which is unavoidable and unpredictable. While in conventional control for robot systems, such noise is removed to the maximum extent, it is now suggested believed that biological systems do not remove the noise but rather make use of it in order to adapt to the environment.

In this study, we propose a novel control method for such a multi–robot system, inspired by the biological fluctuation called the “attractor selection model” [7]. In the future, robots are expected to work in complex and unstructured environments like our daily lives. The attractor selection model is the simplest model of the biological fluctuation, which can realize the adaptation to various environments without any knowledge of the environment model. Therefore our control method is expected to handle a multi-robot system in a dynamic environment without modelling it. We apply the proposed method to the dynamic task assignment of a group of robots and we show the availability of the proposed method.

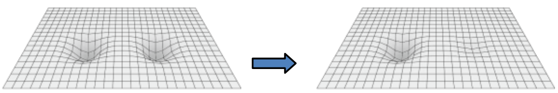
2. Biological Fluctuation

Kashiwagi et al. built a mathematical model of the adaptation mechanism of bacteria-based on a biological fluctuation [7]. This model is called the “attractor selection model" and is the simplest model of animals' control mechanism utilizing noises. Since this mechanism works flexibly and robustly without the model of the target, we propose a task assignment mechanism based on this attractor selection model.

1) *Attractor selection model:* The attractor selection model can be represented by the Langevin equation as:

$$\tau_x \dot{x} = -\frac{du(x)}{dx} A + \varepsilon \qquad (1)$$

where x, τ_x and ε are the state, the time constant and the noise, respectively. (This formulation (1) is not the only way to implement our method, but it is convenient in order to explain the behavior of the attractor selection model.) $u(x)$ is a potential function which has several attractors (local minima), as depicted in Fig.1(a). Each attractor corresponds to candidate solution which would be suitable in some situation, and is designed in advance (genetically-determined). In the attractor selection model, an attractor which is suited to the environment is searched for utilizing noises.



(a) Potential Function **(b) Effective Landscape**

Fig. 1. Attractor selection model

A is a variable called "activity", which indicates the fitness of the state x to the environment, and controls the behavior of the attractor selection model. That is, $u(x)$ becomes dominant in (1) when the activity is large, and the state transition becomes more probabilistic. The activity is designed to be large (small) when the state x is suited (not suited) to the environment. If the activity becomes small (large) in the right (left) area of the Fig.1(a), the potential function is effectively modified as depicted in Fig.1(b). As a result, the state of the system is entrained into an attractor which is suited to the environment where the activity becomes large. Otherwise the activity remains to be small and a suitable attractor is searched for by a random walk.

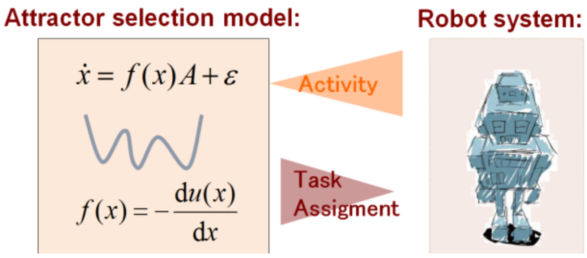


Fig. 2. Block Diagram

The attractor selection model is a method for searching local optima with respect to an unknown potential function utilizing noises. This method finds local optima by adaptively adjusting the effect of noises according to the change of activity. Fig. 2 shows the block diagram of this method.

2) *Robot control using the attractor selection model:* The aim of this research is to develop a task assignment control method for a system which is hard to be modeled due to its complexity or unknown disturbances within the environment. Robot's task assignment process can be regarded as a minimization problem of a potential function which indicates the achievement of the task. Fig 3 represents the potential function of this study.

In this research, we employ a Gaussian mixture model (2) as the potential function:

$$u(a) = -\sum_{i=1}^{N} m_i G_i(a; \overline{a_i}), \qquad (2)$$

where N denotes the number of Gaussians, and m_i is the mixture rate of the i-th Gaussian. $G_i(a; a_i)$ is a Gaussian whose center is a_i and the width is σ respectively, and defined as

$$G_i(a; \overline{a_i}) = (2\pi\sigma^2)^{-D/2} \exp\left\{-\frac{1}{2\sigma^2}\left\|a - \overline{a_i}\right\|^2\right\} \qquad (3)$$

In this case, the center of each Gaussian becomes an attractor. The behavior of this system is such that the state x approaches to the nearest attractor like a point mass with a gravitational pulls from many objects (attractors).

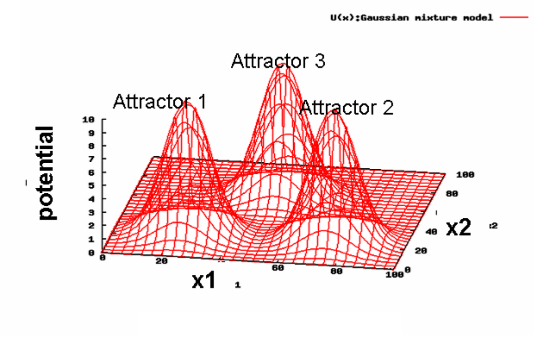


Fig. 3. Potential Function

3) *Activity Design:* In the attractor selection model, the activity controls the behavior of the system. Therefore the system behaves as follows: If the current output task is suited to achieve the desired target situation, the state of the attractor selection model is entrained into an attractor and alters little. Therefore the desired task would be repeated. Otherwise, the state x changes by a random walk and a new desired task control signal is searched for. This can be achieved if the activity is set up such that the

activity becomes large (small) when the current task is suited (not suited). In this study, we employed these equations in order to control the activity behavior:

$$A(t) = -\left(G(t) - G(t-1)\right) \tag{4}$$
$$G(t) = 0.1g(t) + 0.9G(t-1) \tag{5}$$

where g(t) indicates the current entropy level of the dust distribution inside the environment, and G(t) is the entropy average value until time *t*. The activity becomes larger when there are fewer dusts within the environment, while the activity becomes smaller otherwise.

3. Simulation Experiments

To verify our proposed method, we conducted simulation of cleaning tasks for a multi-robot system using the attractor selection model, as shown in Figure 4, 5, and 6.

The environment was designed as a rectangular area of 8m×8m with a trash can at the centre, and a dump area at the upper corner. We built three different versions of the environment in order to perform our experiments with an increasing level of complexity. Fig.4 shows the simplest case where two rooms are placed inside the simulation area, while Fig.5 and Fig.6 show a three and four room configuration. Robots are designed as circles of diameter 0.45m that can move inside the simulation area and detect the dust appeared in the environment. Three kinds of action mode, "Sweeping dust" (Circle), "Taking dust into the trash can" (Square), and "Dumping the dust after carrying it to the dump area" (Triangle), are set as basic action modes for each robot in order to achieve the cleaning tasks.

In addition we gave more realism to our simulation environment introducing dynamical objects in the shape of doors. This gave us the opportunity to see the performance of the attractor selection model against changing situations. Doors open or close a certain amount of times every 1000 time units (frequency value), this feature converts the environment into a constantly changing area. Frequency values are predefined at the beginning of each simulation. We also took into account the possibility of robot breakdown, implementing a case for every simulation configuration where a pair of robots stops working during the process. Finally in order to compare the performance of the attractor selection model we implemented a standard task assignment method called the role fixed model, where each task was assigned to two robots at the beginning of the simulation process, and will not be changed.

We conducted simulation experiments over the three different environments, starting with 6 six robots, and using the following configurations:

Case 1: No dynamic objects were used. (Plain form)
Case 2: Doors were initialized with frequency 2.
Case 3: Doors were initialized with frequency 5.
Case 4: Doors were initialized with frequency 10.
Case 5: Doors were initialized with frequency 15.

The value of parameters used for the simulation experiments is described as follows. The range of detection for dust in the environment is 0.5m, and range of detection for dust in the trash can is 1m. The robot velocity and rotational speed were 1.0km/h and 30deg/s respectively. Ten trials were conducted for each experimental condition, and typical results are shown as

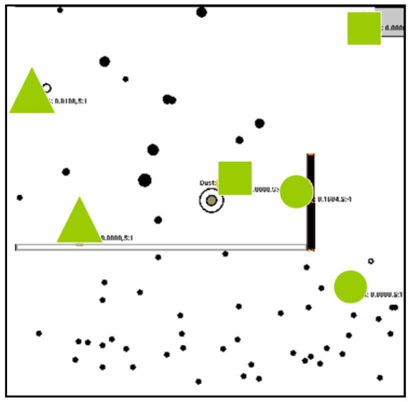


Fig. 4. Environment 1

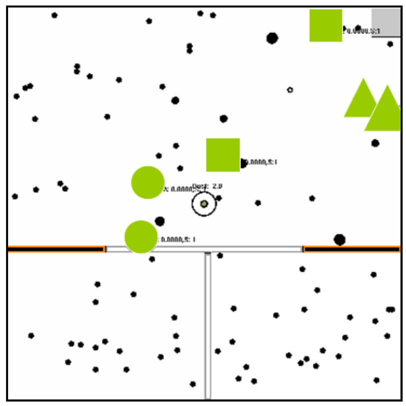


Fig. 5. Environment 2

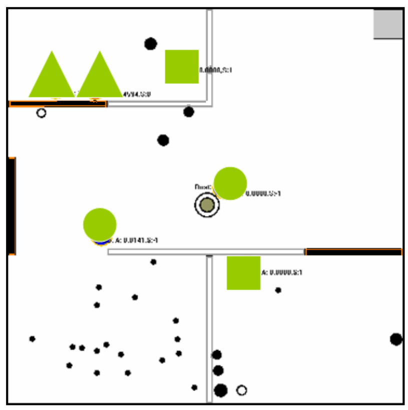


Fig. 6. Environment 3

follows.

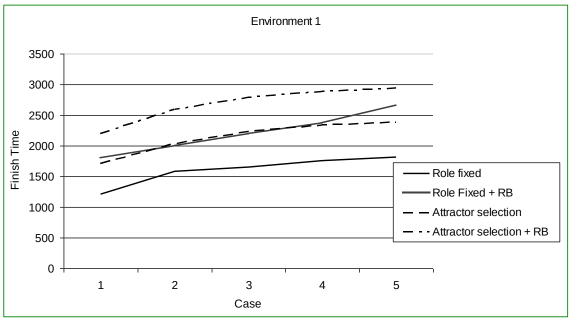


Fig.7. Performances within the environment 1

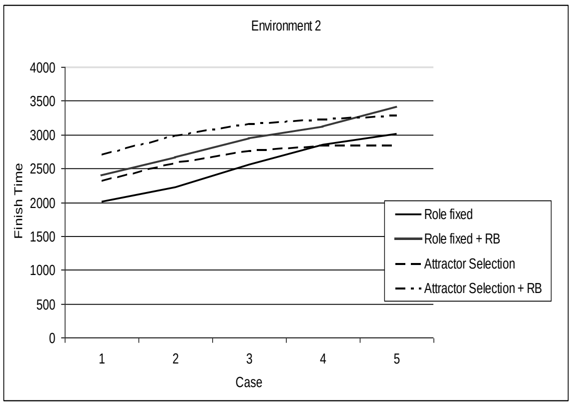


Fig.8. Performances within the environment 2

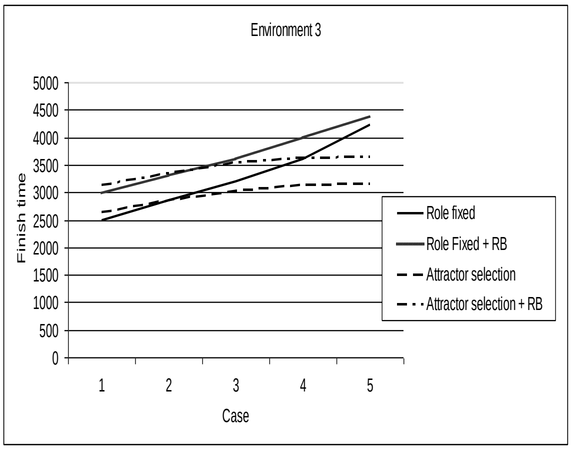


Fig.9. Performances within the environment 3

Fig.7 represents the results for the simplest environment of our simulation, where the role fixed model has a better performance than the attractor selection model in both conditions (with and without robot breakdown). On the other hand Fig.8 and Fig.9 represents the results for both second and third environment respectively, where the previous tendency continues until it reaches a complex point (4^{th} case Fig.8, 2^{nd} case Fig.9), where the role fixed model cannot cope with the complexity of the environment and reduces its performances drastically, while at the same time the attractor selection model issues a better performance.

4. Conclusion and Future Work

From Fig. 7-9, the attractor selection model seems to be better than the role fixed model within relatively complex situations. The finish time using the role fixed model increases as the environment becomes more complex. On the other hand, the finish time value using the attractor selection model is saturated. From these observations we can state that the attractor selection model improves its performance as the environment gets more dynamic and complex, and consequently the attractor selection model adapts itself to the environment better than the role fixed model. In addition the attractor selection model can handle robot breakdowns and hardware failures within complex situations where the other method just reduces its performance drastically.

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